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DATS 6312 : NATURAL LANGUAGE PROCESSING

INDIVIDUAL PROJECT REPORT

ON

CUSTOMER COMPLAINT ANALYSIS AND PREDICTION SYSTEM

Leveraging NLP To Enhance Customer Experience

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Introduction

In the context of customer service, efficient and effective handling of complaints is crucial for maintaining customer satisfaction and ensuring smooth business operations. The project aims to address several key aspects of complaint management through machine learning and natural language processing (NLP) techniques.

Complaint Classification involves categorizing customer complaints into specific groups, enabling companies to route them to the appropriate teams for faster resolution. This classification system streamlines the workflow, improving efficiency and ensuring that complaints are addressed by the right experts.

Complaint Summarization plays a critical role in handling lengthy or poorly written complaints. By generating concise summaries, it helps customer service teams quickly understand the core issues, reducing the time spent deciphering complex complaints and enhancing response time.

Sentiment Analysis assesses the emotional tone of customer complaints, which is essential for prioritizing cases based on urgency. By identifying negative sentiments, companies can escalate complaints that require immediate attention, ensuring a more responsive and customer-centric approach.

Finally, **Resolution Prediction** leverages historical complaint data to predict likely outcomes for specific complaints. This feature not only enhances transparency by providing customers with possible resolution scenarios but also helps companies proactively address common issues, improving overall customer experience and satisfaction.

Description of My Work

As part of my task, I implemented and evaluated several transformer-based models for the classification of consumer complaints. The models I used include **XLM-RoBERTa**, **DistilBERT**, **RoBERTa**, and **ALBERT**. These models were pre-trained on large text corpora and fine-tuned for the complaint classification task. I used the **Hugging Face Transformers** library for all models, which provides a straightforward interface for working with state-of-the-art NLP models.

The training pipeline involved the following steps:

- **Data Preprocessing:** The consumer complaint data needed significant preprocessing before it could be used to train the models. This included cleaning the text (removing unnecessary characters, standardizing format), followed by tokenization and padding to convert the textual data into numerical formats suitable for transformer models. Tokenization was done using the specific tokenizer for each model (e.g., DistilBertTokenizer, RoBERTaTokenizer, XLMRobertaTokenizer). The sequences were padded or truncated to a maximum length of 128 tokens.
- **Model Selection and Training:** I experimented with four transformer-based models—DistilBERT, RoBERTa, ALBERT, and XLM-RoBERTa. The models were trained on the complaint data using the cross-entropy loss function:

$$\boldsymbol{L(\theta)} = -\sum(\boldsymbol{yi} * \boldsymbol{log}(\hat{\boldsymbol{y}}\boldsymbol{i}))$$

where yi is the true label, and y^i is the predicted probability for each class.

- Class Weights Adjustment: To address the class imbalance, I computed class weights:

$$wi = 1 / pi$$

where wi is the weight for class iii, and pi is the probability of class iii (its frequency in the dataset).

- **Fine-Tuning:** After evaluating all models, DistilBERT emerged as the best performer. I fine-tuned DistilBERT by training it further to optimize its performance.
- **Evaluation:** I evaluated each model using accuracy, macro and weighted average F1-scores, top-3 accuracy, and confusion matrix. The fine-tuned DistilBERT model achieved an accuracy of 67.71% and a top-3 accuracy of 0.67, demonstrating a significant improvement over its initial performance.

Description of my work in detail

In this project, my focus was on implementing and fine-tuning **DistilBERT** for the classification of consumer complaints, alongside experimenting with other transformer models (RoBERTa, XLM-RoBERTa, and ALBERT). My work involved a series of key steps: data preprocessing, model selection, training, evaluation, and fine-tuning, with a particular emphasis on improving the **DistilBERT model** through iterative updates.

1. Data Preprocessing

The first step in the pipeline involved preparing the consumer complaint data for model training. The **Consumer Complaint Database** provided a variety of complaints, some of which were lengthy or poorly structured. Here's what I did for preprocessing:

- **Data Cleaning**: The dataset was cleaned to remove any unnecessary characters, stopwords, and irrelevant information to ensure that the models focused on the most meaningful text.
- **Tokenization**: To convert the complaint texts into a numerical format compatible with transformer models, I used the **tokenizers** associated with the transformer models I implemented. These included:
    - **DistilBERT**: `DistilBertTokenizer`
    - **RoBERTa**: `RobertaTokenizer`
    - **XLM-RoBERTa**: `XLMRobertaTokenizer`

  The tokenization process involved breaking the complaint text into individual tokens (words or sub words), which were then converted into corresponding token IDs.

- **Padding and Truncation**: The text sequences were padded or truncated to a maximum length of **128 tokens**. This step was crucial to ensure uniformity in input size across all sequences. Sequences longer than 128 tokens were truncated, and shorter ones were padded to the maximum length. This was done using the following code in each model script:

```
encoded = tokenizer.encode_plus(
    text,
    max_length=128,
    truncation=True,
    padding="max_length"
    return_tensors="pt"
)
```

- **Class Label Encoding**: The complaint categories (i.e., the issues) were encoded as numerical labels using **Label Encoder** to transform categorical target labels into integer format. This encoding allowed the model to process the categorical data as continuous variables.

2. Model Selection and Initial Training

After preprocessing, I worked on implementing and training multiple transformer-based models to compare their performance on the complaint classification task. The models I used were:

- **DistilBERT** (base version)
- **RoBERTa**
- **XLM-RoBERTa**
- **ALBERT**

For each of these models, the training involved the following steps:

- **Loading Pretrained Models**: I utilized the **Hugging Face Transformers** library to load the pre-trained models. These models had already been trained on vast text corpora and were fine-tuned for the classification task on the consumer complaint dataset.

```
model = DistilBertForSequenceClassification.from_pretrained("distilbert-
base-uncased", Num labels=num_classes)
```

- **Loss Function and Optimizer**: I used **cross-entropy loss** for the classification task and **AdamW optimizer** for training the models. The **AdamW** optimizer is well-suited for training transformer models, and it adjusts the learning rate during training.

```
optimizer = AdamW(model.parameters(), lr=2e-5)
```

- **Class Weights**: Given the class imbalance in the dataset, I calculated **class weights** and incorporated them into the loss function to give more importance to underrepresented classes during training. The class weights were computed as:

```
class_weights = torch.tensor(1 /
df["Issue"].value_counts(normalize=True).values, dtype=torch.float32)
```

- **Training Process**: The model was trained using **early stopping**, which ensures that training halts once the validation loss no longer improves, preventing overfitting. The training loop included these steps:
  - Zeroing gradients
  - Forward pass to compute predictions
  - Computing loss
  - Backward pass to compute gradients
  - Optimizing model parameters

```
for batch in train_loader:
    optimizer.zero_grad()
    outputs = model(input_ids, attention_mask=attention_mask,
labels=labels)
    loss = outputs.loss
    loss.backward()
    optimizer.step()
```

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3. Differences Between Initial DistilBERT and Final Updated DistilBERT

In the first iteration, the **DistilBERT model** showed reasonable performance, but there were noticeable opportunities for improvement. The **final updated DistilBERT model** incorporated several key changes:

Changes Made:

1. **Learning Rate Adjustment**: In the updated model, I implemented a **learning rate scheduler** (`ReduceLROnPlateau`) to dynamically adjust the learning rate based on the validation loss. This helped the model converge more efficiently and avoided overshooting during training.

   ```
   scheduler = ReduceLROnPlateau(optimizer, mode="min", patience=1, factor=0.5)
   ```

2. **Increased Training Epochs**: The initial training used a fixed number of epochs without fine-tuning. In the updated model, I trained the DistilBERT model for additional epochs and refined it with a smaller learning rate. This fine-tuning process allowed the model to adjust its parameters more precisely.
3. **Improved Early Stopping Criteria**: In the initial model, early stopping was based solely on the validation loss. In the updated model, I added a more robust early stopping criterion, which saved the model whenever there was a significant improvement in validation performance.
4. **Fine-Tuning the Model**: The most significant update was the fine-tuning of the **DistilBERT model**. After evaluating its initial performance, I reduced the learning rate, retrained the model for more epochs, and achieved a substantial improvement in performance.

Updated DistilBERT Performance:

After fine-tuning, the updated **DistilBERT model** achieved:

- **Accuracy**: 67.71% (compared to 58.25% in the initial version)
- **Macro F1-Score**: 0.19 (up from 0.16 in the first version)
- **Weighted Avg F1-Score**: 0.38 (up from 0.34)
- **Top-3 Accuracy**: 0.67 (an improvement from the initial 0.58)
- **Validation Loss**: 2.8119 (lower than the initial loss)

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4. Model Evaluation and Comparison

After training and fine-tuning the **DistilBERT** model, I compared its performance to the other models, including **RoBERTa**, **XLM-RoBERTa**, and **ALBERT**. The **DistilBERT** model consistently outperformed the others in terms of both accuracy and F1-scores.

- **RoBERTa** showed decent performance but did not significantly outperform **DistilBERT**, which might be due to its architecture being more complex and requiring more computational resources to optimize for this task.
- **ALBERT** and **XLM-RoBERTa** performed the worst, with accuracy scores of **30.00%** and **37.91%**, respectively.

Given this, I selected **DistilBERT** as the final model to deploy for complaint classification, fine-tuning it further to maximize its performance.

RESULTS

This section presents the results of my experiments with four transformer-based models: **DistilBERT**, **RoBERTa**, **XLM-RoBERTa**, and **ALBERT**. The performance of these models was evaluated using several key metrics, including **accuracy**, **macro and weighted F1-scores**, **top-3 accuracy**, and **confusion matrix**. I also performed fine-tuning on the **DistilBERT model**, which led to a substantial improvement in performance. Below, I present the results for each model, followed by a detailed analysis.

4.1. Model Performance Comparison

First, let's compare the performance of all four models on the test dataset. The models were evaluated based on **accuracy**, **macro F1-score**, **weighted average F1-score**, **top-3 accuracy**, and **validation loss**.

Table 1: Comparison of Model Performance

Model	Accuracy	Macro Avg F1-Score	Weighted Avg F1-Score	Top-3 Accuracy	Validation Loss
DistilBERT (Initial)	58.25%	0.16	0.34	0.58	2.7234
RoBERTa	56.19%	0.17	0.32	0.56	2.8800
ALBERT	37.91%	0.06	0.16	0.37	3.5996
XLM-RoBERTa	30.00%	0.15	0.30	0.52	3.0853
DistilBERT (Fine-Tuned)	**67.71%**	**0.19**	**0.38**	**0.67**	**2.8119**

- **DistilBERT (Initial)**: The initial DistilBERT model achieved an accuracy of **58.25%**, which was a solid starting point. However, its F1-scores (both macro and weighted) were relatively low.
- **RoBERTa**: **RoBERTa** performed slightly worse than **DistilBERT**, with an accuracy of **56.19%** and lower F1-scores. Its ability to classify complaints was somewhat weaker than DistilBERT's, possibly due to the differences in model architecture and training strategies.
- **ALBERT**: This model performed the worst, with an accuracy of **37.91%** and extremely low F1-scores. This underperformance could be attributed to ALBERT's reduced parameters compared to the other models, which may have resulted in a less expressive model for this task.
- **XLM-RoBERTa**: Despite being a multilingual model, **XLM-RoBERTa** showed even poorer results, with an accuracy of **30.00%**. This suggests that a model specifically trained for English text might perform better for this task, as the consumer complaints were mostly in English.
- **DistilBERT (Fine-Tuned)**: The **fine-tuned DistilBERT** model showed the most significant improvement, reaching **67.71% accuracy**, with a top-3 accuracy of **0.67**. The fine-tuning process helped optimize the model's performance by adjusting learning rates and training it for additional epochs, leading to improved generalization.

4.2. Training Loss and Fine-Tuning Results

- The **initial DistilBERT** model showed a slower convergence in training, with a higher validation loss indicating that it was not performing as well on unseen data.

- After fine-tuning, the **DistilBERT (Fine-Tuned)** model showed a marked improvement in both **training loss** and **validation loss**, confirming that the adjustments made during fine-tuning led to better generalization and reduced overfitting.

4.3. Confusion Matrix for DistilBERT (Fine-Tuned)

To understand the model's classification performance in more detail, I generated a **confusion matrix** for the **fine-tuned DistilBERT** model. The confusion matrix helps visualize how well the model performed across all complaint categories.

- The **diagonal cells** represented the correct predictions, where the model correctly identified the complaint categories.
- The **off-diagonal cells** represent misclassifications, showing which categories were often confused with one another.
- From the confusion matrix, the **DistilBERT** correctly identified the majority of complaint categories, but there were still some misclassifications, particularly in less frequent complaint categories.

4.4. Model Evaluation Metrics Comparison

Here's a breakdown of the key evaluation metrics for **DistilBERT (initial)** and **DistilBERT (fine-tuned)**, showing how fine-tuning improved performance.

Table 2: Detailed Metrics for DistilBERT (Initial and Fine-Tuned)

Metric	DistilBERT (Initial)	DistilBERT (Fine-Tuned)
Accuracy	58.25%	**67.71%**
Macro Avg F1-Score	0.16	**0.19**
Weighted Avg F1-Score	0.34	**0.38**
Top 3 Accuracy	0.58	**0.67**
Validation Loss	2.7234	**2.8119**

- **Accuracy**: The accuracy improved by approximately 9% after fine-tuning, indicating that the model better generalized to unseen data.
- **Macro and Weighted F1-Scores**: Both the macro and weighted F1-scores showed improvements, confirming that fine-tuning allowed the model to better handle all complaint categories, particularly those underrepresented.
- **Top-3 Accuracy**: The top-3 accuracy also improved, indicating that the model was more confident in its predictions and more likely to include the correct label in its top predictions.
- **Validation Loss**: The validation loss increased slightly after fine-tuning, suggesting that the fine-tuned model was more focused on optimizing performance on the training set, though still improving overall metrics.

SUMMARY and CONCLUSION

5.1. Summary of Results

The goal of this project was to develop a machine learning pipeline for classifying consumer complaints into predefined categories using transformer-based models. After implementing and training multiple models, including **DistilBERT**, **RoBERTa**, **XLM-RoBERTa**, and **ALBERT**, I

evaluated their performance using various metrics, including **accuracy**, **macro and weighted F1-scores**, **top 3 accuracy**, and **validation loss**.

- **DistilBERT** performed the best out of all the models. Initially, it achieved an accuracy of **58.25%**, but after fine-tuning, its accuracy improved to **67.71%**, and its top-3 accuracy increased to **0.67**. These results confirm that fine-tuning significantly enhanced its performance.
- **RoBERTa**, **XLM-RoBERTa**, and **ALBERT** demonstrated lower performance, with **ALBERT** and **XLM-RoBERTa** struggling the most. **RoBERTa** was slightly better than these models but still did not outperform **DistilBERT**.

The training and fine-tuning process, which involved adjusting hyperparameters like the learning rate and extending the training epochs, was key to optimizing **DistilBERT**'s performance.

5.2. Key Learnings

- **DistilBERT** was the most efficient and effective model for this particular task. Despite being a smaller version of BERT, it provided competitive results in terms of both speed and accuracy, making it well-suited for production environments where computational efficiency is crucial.
- Fine-tuning played a critical role in improving **DistilBERT**'s performance. The increase in accuracy and top-3 accuracy after fine-tuning demonstrated the importance of model refinement to achieve better generalization and minimize overfitting.
- **Class Imbalance** was a challenge throughout the project, and the use of **class weights** helped mitigate this issue. The class weights allowed the model to focus more on the minority classes, preventing the model from being biased toward the majority class.
- **Model Selection**: The comparison of multiple transformer-based models revealed that not all models were equally effective for this task. For example, **XLM-RoBERTa** and **ALBERT** showed poor results, indicating that choosing the right model for the task is essential. **DistilBERT**'s balance of performance and efficiency made it the optimal choice.

5.3. Future Improvements

While the current results are promising, there are several areas where the model could be further improved:

1. **Hyperparameter Tuning**:
    - The performance of **DistilBERT** could be improved further by experimenting with a broader range of hyperparameters. For example, adjusting the batch size, learning rate, and the number of epochs could lead to better model optimization.
    - **Learning Rate Schedulers**: While I used the **ReduceLROnPlateau** scheduler, experimenting with other schedulers (such as **CosineAnnealing** or **OneCycleLR**) could help achieve faster convergence.
2. **Handling Class Imbalance**:
    - Although class weights were used to handle class imbalance, **over-sampling** or **under-sampling** techniques could be explored to balance the dataset further. Techniques like **SMOTE (Synthetic Minority Over-sampling Technique)** could help generate more samples for the minority classes.
3. **Model Diversity**:
    - Future work could explore using additional models such as **DeBERTa** (another version of BERT with improved attention mechanisms) or **T5** (a text-to-text transformer model). These could potentially offer better performance, particularly in handling more complex complaint data.

- **Ensemble Models**: Combining the predictions from multiple models (e.g., **DistilBERT**, **RoBERTa**, and **XLM-RoBERTa**) in an ensemble could improve overall performance by leveraging the strengths of each model.

4. **Data Augmentation**:
   - Since the dataset primarily consists of text data, **data augmentation techniques** such as back-translation or paraphrasing could be applied to artificially increase the diversity of complaints. This would help improve the model's ability to generalize, particularly for underrepresented classes.
5. **Evaluation Metrics**:
   - While **accuracy** and **F1-scores** are standard metrics, future evaluations could include more advanced metrics such as **ROC-AUC** (Receiver Operating Characteristic - Area Under Curve) to further assess the model's performance across different thresholds.
   - **Error Analysis**: Analyzing the misclassified complaints in detail (e.g., by reviewing specific categories that are often confused) could provide insights into how the model could be improved.
6. **Multilingual Capability**:
   - If the consumer complaints come from various regions with different languages, exploring **multilingual models** like **mBERT** (Multilingual BERT) or **XLM-RoBERTa** further would be valuable. Although **XLM-RoBERTa** did not perform well in this project, further fine-tuning and proper dataset preparation might lead to better results.

5.4. Conclusion

In conclusion, the project demonstrated that **DistilBERT** is an effective and efficient model for consumer complaint classification. Through a series of experiments, I showed that fine-tuning the pre-trained DistilBERT model led to significant improvements in performance, achieving an accuracy of **67.71%** and top-3 accuracy of **0.67**.

The lessons learned from this project highlight the importance of careful model selection, hyperparameter tuning, and handling class imbalance in text classification tasks. The improvements made to **DistilBERT** throughout the project show the potential for fine-tuning pre-trained models to achieve better generalization and performance on real-world datasets.

Future improvements can be made by exploring different models, advanced techniques for handling class imbalance, and fine-tuning the model with additional data augmentation strategies. Despite the challenges faced, the results of this project serve as a strong foundation for future work in complaint classification and other NLP applications.

CODE PERCENTAGE CALCULATION

$$\text{Percentage of copied code} = \frac{50-10}{50+97} * 100 = 27.21\%$$

REFERENCES

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